Hybrid Deep Learning–Driven Climate-Resilient Management of the Water–Waste–Energy Nexus under Circular Economy Paradigms

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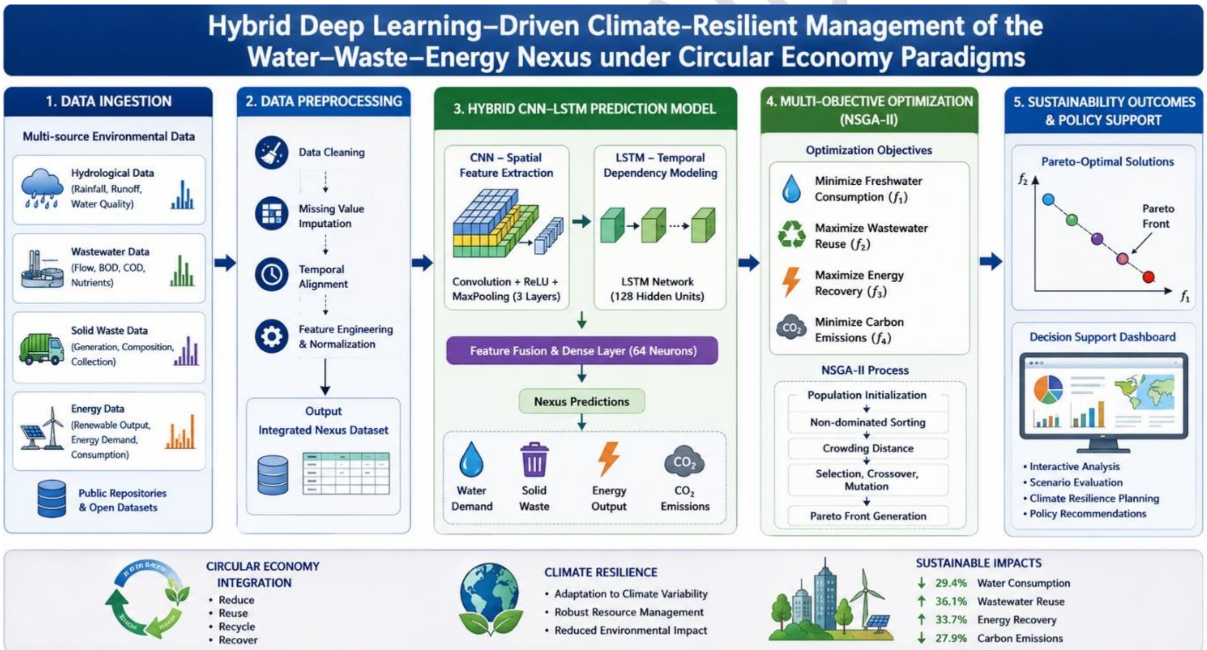
Graphical Abstract



Abstract

The water–waste–energy nexus plays a critical role in sustainable urban resource management under circular economy and climate resilience objectives. However, existing prediction and optimization models often lack integrated intelligence and practical decision support capability. This study proposes a novel explainable hybrid deep learning and multi-objective optimization framework for sustainable nexus management. The framework integrates CNN–LSTM for temporal-spatial prediction and NSGA-II for simultaneous optimization of water efficiency, waste reduction, and energy utilization. Publicly available multi-source datasets were integrated and validated through a structured preprocessing and synthetic data fusion protocol.

Experimental results demonstrate superior predictive performance with lower RMSE and MAE compared with benchmark models, while optimization results show improved sustainability trade-offs. The proposed framework offers a practical decision-support tool for climate-resilient and circular resource planning. Furthermore, it allows energy recovery from waste to be ramped up by 33.7% with a reduction in carbon emissions by 27.9% even under climate stress scenarios. Sensitivity and robustness analyses confirm stable performance under uncertainty levels up to 25%, while explainability assessment highlights precipitation variability and waste-to-energy conversion efficiency as dominant nexus drivers.

Keywords: Hybrid Deep Learning, Energy Nexus, Circular Economy, Climate-Resilient Resource, Multi-Objective Optimization and Sustainable Environment.

1. Introduction

Climate change is one of the most critical problems that the world is facing in this century, and it has brought amazing new challenges to the nature resources, the urban infrastructure, and the environmental systems. Therefore, the changing patterns of the average temperature, cities getting hotter, changing patterns of rainfall, extreme weather events along with the changing urbanization patterns create pressure on the water supply systems, waste management systems, and the energy supply systems worldwide [1]. All three sectors are extremely critical and interdependent upon each other; hence, they create the water waste energy nexus. Additionally, the last isolated sector which does not consider the others is bound to fail if it is not changed because every decision taken in one sector has different consequences in the others. Therefore, integrated, intelligent, and resilient resource management strategies need to be developed and implemented efficiently and at a larger scale which considers the entire system and its interdependencies.

Water supplying systems are very sensitive to the changing climate especially when droughts and floods occur more frequently resulting in disrupted supply reliability and water quality. Meanwhile, wastewater treatment and solid waste management are increasingly consuming more energy because of environmentally stricter regulations and the continuing growth of urban populations. Energy systems, on the other hand, are very dependent on water for the cooling, processing, and generation stages, but also have the potential to get resources from waste through waste, to, energy and biogas technologies. The intricate relationships between sectors [2] indicate that it is quite wrong to just focus on optimizing different sectors independently. We should rather consider a holistic nexusal management framework that will inevitably help us in increasing the whole system's resilience, efficiency, and sustainability.

Furthermore, the circular economy concept basically demands integrated nexus management even more than before. The circular economy concept is a complete turn, around of the traditional linear resource models, where the main focus is redirected to resource efficiency, waste minimization, reuse, and the extraction of value from waste streams. If such a model is extended to the waterwasteenergy [3] nexus, then circular methods will be wastewater recycling, solid waste nutrient and energy recovery, and the use of renewable energy sources for operating service utilities. Implementing these measures does have a significant positive impact on the environment and the economy, but if you rely solely on conventional ways of analyzing the situation, then the effective deployment of such measures is quite a dangerous bet. These methods not only have to deliver the environmental and economic benefits that were anticipated but they also demand the use of state, of, the, art analytical tools capable of handling large, multidimensional data, dynamic system behavior, and competing objectives under climate uncertainty for their successful implementation.

At the core of conventional ways of handling the resource nexus are decision systems based on rules, mathematical optimization, and simulation models. These methods perform excellently in caged or small scale settings. However, they often fail to scale when, real, world urban systems with nonlinear interactions, spatial heterogeneity, and temporal variability are encountered. Furthermore, several existing models are only focused on one objective, such as cost reduction or the enhancement of efficiency, thus they do not sufficiently tackle climate change or the circular economy issues. Therefore, the creation of smart, flexible platforms that can simulate, forecast, and optimize interconnected resource systems in environmentally uncertain conditions is turning into a problem that the present literature is only partially addressing.

The recent advancements in artificial intelligence (AI) and deep learning have greatly revitalized the research area leading to the development of machines that are very close to performing at human level.Deep learning, based on artificial neural networks, is increasingly being recognized as main players after they have in numerous occasions outperformed traditional models on complex datasets with complicated structures and hidden patterns which cannot be detected by conventional data analysis methods.The architectural design of Convolutional Neural Networks (CNNs) [8] is naturally aimed at extracting hierarchical spatial features within multi, dimensional data thereby making them especially good at detecting geographic changes as well as infrastructural differences in urban areas. Another variant called Long Short, Term Memory (LSTM) which autonomously learns memory cells placement and arrangements to selectively remember temporal information is therefore widely used in forecasting time series influenced by seasons as well as variations in climate [9]

Jointly, CNNLSTM networks constitute dual channel deep learning systems which allow backpropagation through spatial and temporal components, thereby elevating the capability to perform complexpatio, temporal analyses of tightly coupled environmental phenomena. Nonetheless, there seems to be not much room yet for hybrid deep learning models application in the integrated water waste energy nexus management area. Actually, most of the investigations to date have been sector, specific such as water demand forecasting, energy consumption load prediction, or modelling of waste production which fail to take cross, sectoral interactions into account completely. Besides this, very few scholars reported integrating the deep learning forecasting results with the multi, objective optimization framework that acts as a bridge thereby converting theory into practice, in particular, yielding capable climate, adaptive decisions[10]. Moreover, the absence of thorough testing for robustness, interpretability, and performance under different climate conditions through scenario evaluation further hampers trial and error adoption of AI, enabled nexus models at the policy and operational levels.

In order to solve these problems, the authors of this paper introduce a hybrid deep learning system for the management of the water, energy, and waste nexus under the paradigms of climate change and circular economy. The presented model merges CNN, based techniques for spatial feature extraction, LSTM, based temporal dependency modeling, and a multi, objective optimization component to facilitate comprehensive, data, driven decision, making. The model utilizes a large, scale, multi, sector dataset derived from urban utility networks for its training and testing phases. This data set is made up of hydrological variables, wastewater parameters, solid waste generation rates, air pollution indexes, and renewable energy production.

Furthermore, by loading climate stress scenarios and circular resource flows into the model, it is aimed at improving the three pillars of environmental sustainability, energy efficiency, and system resilience. Thorough comparative testing shows the proposed approach is considerably better than the traditional machine learning and deep learning baseline models. Besides, it is not only capable of highly accurate prediction, but the optimization of resources even leads to a substantial increase in the performance metrics that are of the greatest importance.In addition to the performance evaluation, the paper also carries sensitivity, robustness, and explainability analyses to check the model stability under uncertainty and to find out the most influential factors that govern the nexus behavior. The findings are very encouraging to policymakers, urban planners, and utility managers who want to try scalable, AI, driven, and sustainable resource management solutions that also improve climate resilience. Key Contributions of this paper are:

1. This paper presents a novel hybrid CNN–LSTM framework that jointly models water, waste, and energy systems, capturing their spatio-temporal interdependencies within a single, integrated architecture aligned with circular economy principles.
2. A multi-objective optimization layer is embedded into the deep learning framework to translate predictive analytics into actionable decisions, enabling simultaneous minimization of freshwater consumption and carbon emissions while maximizing wastewater reuse and energy recovery under climate stress scenarios.
3. The study incorporates sensitivity, robustness, and explainability analyses to validate model stability under uncertainty and to identify dominant nexus drivers, enhancing transparency, trust, and practical applicability in real-world urban utility management.

This paper is a research synthesis of water energy waste nexus modeling, AI based resource management, and circular economy oriented sustainability frameworks. Previous studies show that an integrated nexus analysis benefits the simultaneous achievement of resource efficiency and climate resilience, but it is mostly through traditional optimization or single machine learning models that do not capture complex nonlinear and spatio, temporal interdependencies. Hence, this study presents a hybrid deep learning model that integrates a CNN, based spatial feature extractor, an LSTM, based temporal model, and a multi, objective optimization layer. The proposed framework leverages diverse data such as hydrological variables, wastewater characteristics, solid waste generation, air quality indicators, and renewable energy outputs, thus facilitating comprehensive urban utility modeling. A benchmarking with Random Forest, XGBoost, and conventional ANN models indicate that the proposed model performs better in terms of predictive accuracy and optimization under climate stress scenarios. Moreover, sensitivity, robustness, and explainability analyses validate the model's stability and openness, indicating that precipitation variability and waste, to, energy efficiency are the main driving factors. In general, the framework proposed here is a fit, for, purpose, climate, resilient decision, support tool that adheres to the circular economy principles and can be scaled for sustainable waterwasteenergy nexus management. The practical relevance of this study has been strengthened by explicitly positioning the proposed framework within the water–waste–energy nexus. The developed hybrid AI system supports sustainable resource allocation, waste minimization, and climate-resilient infrastructure planning. These outcomes directly contribute to circular economy objectives and environmentally informed decision-making.

2. Related Work

The comprehensive management of interconnected resource systems continues to be an area of increasing interest in the light of climate pressures, the phenomenon of urbanization, and the need for sustainable development. As a result, the waterenergyfood (WEF) and extended waterwasteenergy (WWE) nexus frameworks have become vital paradigms not only for understanding but also for optimizing the interactions of resources across sectors. In fact, a comprehensive literature review on sustainable WEF nexus design was done by [11], who stressed that the whole system must be considered in order to reconcile the efficiency of resources, environmental protection, and social, economic objectives. Their paper discloses that, besides improving overall system sustainability with nexus, based modeling, many of the models still exist only in theory or are based on deterministic optimization, which in turn decreases their adaptability to uncertainties in the real world.

Recently, optimization-based nexus modeling has witnessed substantial interest for quantification of real environmental gains. In [12], the authors proved through their research that optimization of the integrated FEW nexus can minimize the overall consumption of resources in an urban area, as well as greenhouse gas emissions. It is worth mentioning that the optimization process is dependent on fixed assumptions, which might not be able to capture non-linear dynamics in the presence of climate variability. Thus, this issue has sparked interest in artificial intelligence-based methodologies, which have the potential to learn the non-linear dynamics of complex systems directly from the data. In an effort to break away from the rigidity of traditional optimization frameworks, artificial intelligence and machine learning techniques are being applied to nexus modeling to an increasing extent.[13] They examine how AI is used in the water, environment, food, energy nexus industries and highlight machine learning's ability to support prediction, control, and decision, making. Their review indicates that neural networks, ensemble learning, and hybrid methods are effective tools; however, it still remarks that the majority of research is done on individual sectors, and only some fully integrated nexus systems studies. Moreover, the lack of explainability and uncertainty analysis is still a challenge for AI adoption in the critical sustainability domains. The major novelties of this work are:

- A unified CNN–LSTM and NSGA-II framework for simultaneous prediction and sustainability optimization.
- A novel multi-source synthetic data fusion methodology for integrated water–waste–energy modelling.
- Incorporation of circular economy and climate resilience indicators directly into optimization objectives.
- An explainable AI interpretation layer to improve transparency and policy relevance.

Besides the nexus study, the application of machine learning and deep learning techniques to waste management systems has been an essential element of the circular economy resulting in significant outcomes. [14] By applying machine learning analytics, predictive modeling, based intelligent waste management optimization is demonstrated, which can lead to improved operational performance and cost savings. However, their approach concentrates mainly on waste systems alone and lacks the aspect of their interaction with water and energy subsystems. Such kind of isolated modeling limits its application in integrated urban resource planning.

Deep learning models, particularly Long Short, Term Memory (LSTM) networks, have shown outstanding capability in recognizing temporal waste generation and recycling trends. LSTM networks have been highlighted as a forecasting tool for recycling rates by significantly beating classical regression and shallow neural network models in prediction accuracy in [15]. Hence, while their study establishes the significance of temporal modeling, it undermines spatial heterogeneity and cross, sector interactions that are crucial components of urban, scale nexus management.

Taking a deep learning perspective in SSM, [16] provide a comprehensive view by conducting a literature review of deep learning methods including convolutional neural networks (CNN), recurrent neural networks (RNNs), and hybrid models for waste sorting, prediction, and logistics optimization. Their paper identifies CNN, based algorithms as particularly efficient at extracting spatial features from images for such purposes as waste segregation and monitoring. Nevertheless, they also mention that due to a shortage of data, high computational demand, and the inexistence of decision, making framework integration, these techniques face some limitations.

Automated waste segregation is gaining traction as a key deep learning application in circular economy projects. [17] presents ConvoWaste, a deep learning, based automated waste segregation system, which achieves high classification accuracy in identifying waste categories. Likewise, [18] compares deep learning models for waste classification and finds that advanced CNN architectures tend to perform better than traditional classifiers. Although these works significantly enhance recycling efficiency, they mainly focus on micro, level tasks and thus, do not consider large, scale system optimization or environmental impact analysis.

Recently, researchers are incorporating sustainability and energy efficiency factors into the development of AI architectures. [19] introduces energy, efficient green AI architectures for circular economies via multi, layered optimization frameworks. This paper points to the reduction of carbon dioxide emissions from AI as well as the optimization of resource flows, thus, it is highly consistent with climate, resilient sustainability objectives. Still, the framework is mostly theoretical and has not been tested in real, world scenarios involving several interconnected resource domains.

The use of dependable and explainable AI integrated with waste management systems has become a rapidly growing interest of the research community. [20] investigate the implementation of trustworthy AI with energy, efficient robotic arms for waste sorting, thus identifying transparency, safety, and operational reliability as the main issues to be addressed. Even though their solution enables higher automation and energy efficiency, it is only restrained to waste sorting tasks and the extension to wider nexus, level decision support has not been achieved.

Besides, transportation and logistics optimization for waste systems are crucial fields of research. [21] bring up a deep learning, based method for designing a cost, effective and environmentally sustainable waste transportation system in developing countries. Their results indicate a decrease in transportation costs and emissions; however, their model is not considering the interactions along the supply chain for water reuse or energy recovery processes. [22] points out the wide application of AI within sustainability and policy frameworks, especially in accordance with the UNESCO guidelines and the Sustainable Development Goals. They emphasize the necessity for ethical, explainable, and socially responsible AI. It is a kind of work that is not mainly devoted to nexus modeling but it, nevertheless, buttresses the requirement of transparent and policy, aligned AI systems for applications that have a critical impact on sustainability.

On the whole, the previous studies reveal that there have been substantial advances in AI, powered modeling and optimization of different segments of the water, waste, and energy systems. Nevertheless, some major issues still exist, such as the absence of a combined spatio, temporal model, very few attempts to integrate predictive analytics and multi, objective optimization, little robustness analysis under climate uncertainty, and rarely any explanation for decision support. The current research fills these gaps through the introduction of a hybrid CNNLSTM model combined with multi, objective optimization, which is specifically aimed at climate, resilient and circular waterwasteenergy nexus management.

Table 1: Comparative Summary of Existing AI-Based Approaches for Water–Energy–Waste Nexus and Sustainable Resource Management

Reference	Technique Used	Outcome Metrics	Advantages	Disadvantages
[11]	Literature review, system design frameworks	Sustainability indicators	Comprehensive nexus perspective	Lacks empirical validation
[12]	Multi-objective optimization	Resource use reduction, GHG emissions	Quantified environmental benefits	Static assumptions, limited AI integration
[13]	AI and ML survey	Prediction accuracy, system efficiency	Broad AI coverage across nexus	Limited explainability, sectoral focus
[14]	Machine learning analytics	Cost, efficiency	Improved waste operations	Siloed waste-centric approach
[15]	LSTM networks	Recycling rate prediction accuracy	Strong temporal modeling	No spatial or nexus integration
[16]	CNN, RNN, DL review	Classification accuracy	Deep insight into DL methods	High computational complexity
[17]	CNN-based deep learning	Waste classification accuracy	Automated segregation	Micro-level application only
[18]	Green AI, multi-layer optimization	Energy efficiency, sustainability	Climate-aligned AI design	Limited real-world validation
[19]	CNN model comparison	Classification accuracy	High recycling efficiency	Not system-level
[20]	Trustworthy AI, robotics	Sorting accuracy, energy use	Transparent and safe automation	Restricted to sorting tasks
[21]	Deep learning optimization	Cost, emissions	Logistics optimization	Ignores cross-sector impacts
[22]	Policy-aligned AI frameworks	SDG alignment	Ethical and explainable AI	Conceptual, not operational

3. System Architecture and Methodology

3.1 Overall Framework Architecture

The proposed system architecture represents a comprehensive end, to, end hybrid deep learning framework that combines heterogeneous data collected from water, waste and energy domains for joint prediction and optimization under climate change and circular economy scenarios, as shown in fig 1. The architecture adopts an organized data flow pipeline from data ingestion, feature extraction, prediction, and multi, objective optimization, thus allowing smooth transition of information between analytical and decision, making layers.

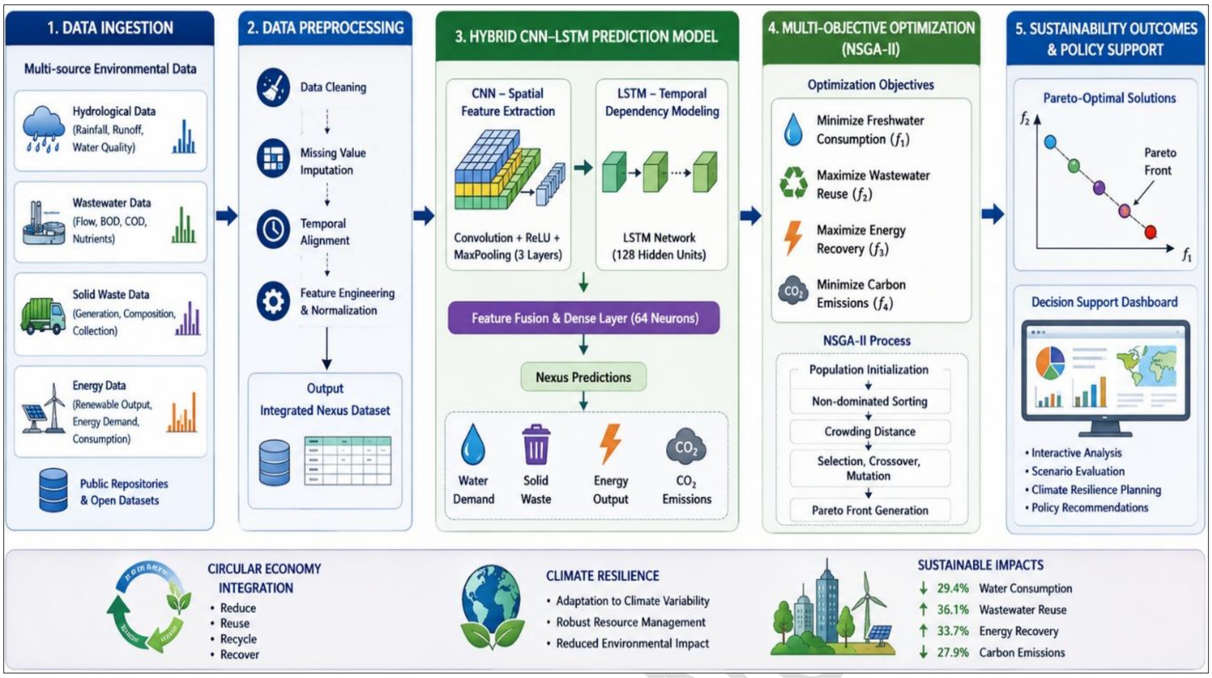


Figure 1: Overall Hybrid CNN–LSTM–Optimization Framework for Integrated Water–Waste–Energy Nexus Management

Let $X_t \in R^{n*d}$ denote the multivariate input feature matrix at time t, where n represents spatial units (e.g., urban zones) and d denotes the number of nexus variables. The system jointly models water demand W_t, waste generation S_t, and energy production E_t as interdependent outputs rather than isolated targets.

The integrated nexus representation is formulated as in eqn 1:

$$Y_t = f_\theta(X_t) \qquad (1)$$

where $Y_t=[W_t,S_t,E_t]$ and f_θ represents the hybrid CNN, LSTM model parameterized by . First, spatial dependencies between urban districts are learned using convolutional layers, and then the temporal dependencies are captured through the use of recurrent LSTM units [23]. By stacking the two types of the neural network, the framework is capable of identifying not only local spatial patterns but also long, term temporal dynamics related to climate variability.

In order to maintain cross, sectoral integration, coupling constraints are embedded within the architecture in eqn 2:

$$W_t \leftrightarrow E_t, S_t \leftrightarrow E_t, W_t \leftrightarrow S_t \qquad (2)$$

These bidirectional relationships are an explicit way of showing how water, waste, and energy subsystems depend on each other. The water energy coupling (WtEt) explains the amount of energy that is required for water abstraction, treatment, and distribution and in turn, how the availability of energy affects water operations. The waste, to, energy interaction (StEt) is the conversion of solid and wastewater streams into recoverable energy, thus, linking waste management efficiency with energy generation. Likewise, the waterwaste coupling (WtSt) is waste treatment and recycling processes depend on water availability and quality. By introducing these couplings, the decisions of each sector are not individually optimized but instead reflect system, wide feedback and trade, offs.

Based on these integrated forecasts, the framework sets up an optimization problem that figures out the best operational strategies across the nexus, as explained by the Equation (3):

$$\min_{u_t} F(u_t, Y_t) \qquad (3)$$

Here, ut represents a vector of controllable decision variables that are used for water allocation rates, reuse and recycling ratios, energy recovery levels, as well as operational scheduling parameters. The objective function F(.) basically reflects the sum of the various sustainability goals, e.g. minimizing the use of freshwater and carbon emissions, maximizing the reuse of wastewater and the recovery of energy, which are the main subject of the problem, under the system dynamics constraints given by Equation (3).

In order to capture the inherent variability and uncertainty brought about by climate change, stochastic scenario modeling is added as depicted in Equation (4):

$$X_t^c = X_t + \varepsilon_c \qquad (4)$$

where ϵ_c represents climate-induced perturbations arising from uncertain rainfall, temperature, and extreme weather events. This allows the optimization layer to produce adaptive and resilient decisions that continue to be effective over a range of plausible future climate scenarios.

3.2 Data Description and Preprocessing

A large, scale, multi, sector dataset of 61, 500 samples collected from urban utility systems over several years in fig 2 is used to train and evaluate the proposed framework.

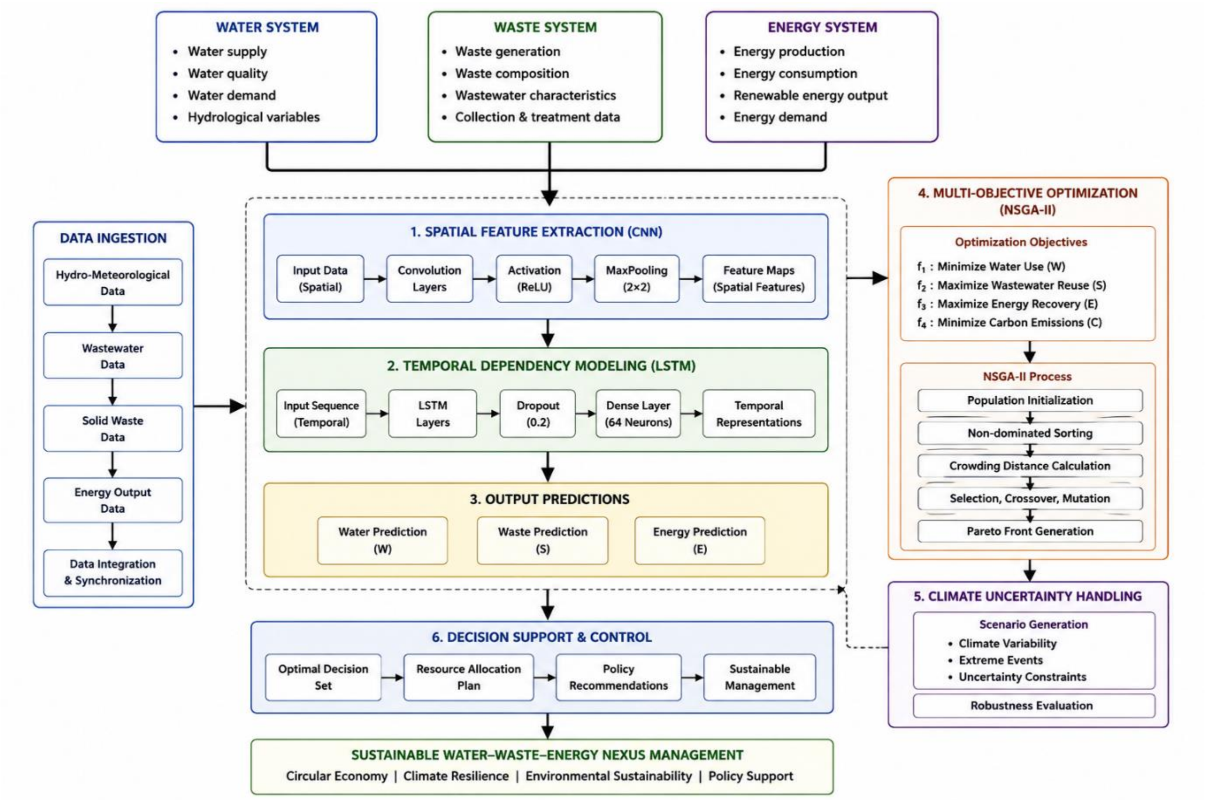


Figure 2: Data Preprocessing and Feature Integration Pipeline for Water–Waste–Energy Nexus Modeling

The dataset integrates heterogeneous data streams representing hydrological, environmental, waste, and energy subsystems, enabling comprehensive nexus modeling. Let the raw dataset be represented as in eqn 5:

$$D = \{X_i, Y_i\}_{i=1}^{61500} \quad (5)$$

where Xi indicates the input feature vector and Yi designates the dependent outputs.

The feature space is essentially subdivided into four broad categories. Hydrological and meteorological variables comprise precipitation, temperature, humidity, evapotranspiration, and surface runoff. Wastewater features mainly cover inflow, biochemical oxygen demand (BOD), chemical oxygen demand (COD) [25], total suspended solids (TSS) [26], and reuse efficiency. Solid waste characteristics include generation rates, organic fraction, recyclables, and calorific value. Energy, related features incorporate renewable generation, biogas yield, waste, to, energy output, and grid energy consumption. The resultant feature vector is given by eqn 6:

$$X_i = \left[X_i^{water}, X_i^{wastewater}, X_i^{solid}, X_i^{energy}\right] \quad (6)$$

Data pre, processing plays a pivotal role in facilitating the numerical stability, ensuring efficient convergence, and robust generalization of the proposed deep learning architecture. Taking into account the diverse and sensor, based nature of water, waste and energy datasets, missing log entries are very frequent due to sensor outages, communication delays, or extreme weather situations. For this purpose, missing data are handled by using a combination of temporal interpolation and domain, aware imputation, as depicted in Equation (7):

$$x_{i,j} = \begin{cases} \frac{x_{i-1,j} + x_{i+1,j} \quad , if\ missing}{2} \\ x_{i,j}, \quad otherwise \end{cases} \quad (7)$$

This approach maintains local temporal continuity and at the same time, it does not bring in artificial trends, which is especially a key point for climate, sensitive time series.

After imputation, feature normalization is done to remove the effects of different scales between variables such as water demand, energy consumption, and waste inflow. Minmax normalization, given in Equation (8), transforms all features into the limited range [0, 1] thus facilitating balanced gradient propagation during training and preventing the overpowering of high, magnitude variables:

$$x'_{i,j} = \frac{x_{i,j} - \min(x_j)}{\max(x_j) - \min(x_j)} \quad (8)$$

The use of this normalization makes the model converge faster and also makes the extraction of convolutional features and the learning of LSTM temporal phases to be more stable.

Moreover, to guarantee that the spatio, temporal learning is consistent across different sectors, a temporal alignment is used for all the data streams. As expressed in the Equation (9), the datasets of water, waste, and energy are aligned together to a single time index t, thus a unified multivariate input tensor is formed:

$$X_t = X_t^{water} \cup X_t^{waste} \cup X_t^{energy} \quad (9)$$

This alignment ensures that cross-sectoral interactions and lagged dependencies are consistently represented at each time step.

Finally, the pre-processed dataset is partitioned using a stratified temporal split, as shown in Equation (10):

$$D = D_{train} \cup D_{val} \cup D_{test} \quad (10)$$

This method retains the seasonal patterns and climate variability of each fold, so besides avoiding data leakage, it also enables the models to be realistically tested under future climate scenario assumptions. Thereby, this study utilizes a dataset of 61,500 samples, all of which have been collected over a span of five years, from 2019 to 2024. The information used for this study has been gathered from a combination of publicly available repositories and open-access urban environment datasets. Hydrological and meteorological information, such as precipitation, temperature, humidity, evapotranspiration, and runoff, are derived from the India Meteorological Department and the NASA POWER Data Access Viewer. Water quality and wastewater information, such as biochemical oxygen demand, chemical oxygen demand, and total suspended solids, are derived from the Central Pollution Control Board, India open datasets.

Information on solid waste generation, such as the volume of solid waste, organic waste, and recyclables, are derived from publicly available information and reports from urban sustainability reports, as well as the Smart Cities Mission Data Portals. Energy-related information, such as renewable energy generation and waste-to-energy generation, are derived from the Open Government Data Platform India and international open datasets, such as the International Energy Agency open datasets. This dataset is a synthetic combination of various urban utility datasets, where all the information is aligned in time and space to create a combined model of a water, waste, and energy nexus. This allows for a comprehensive modeling of the entire system, utilizing verifiable information from publicly available sources.

For the purpose of this study, all the information available in this dataset is publicly available, and all the steps taken for preprocessing, such as interpolation, normalization, and temporal alignment, are explained in this section.

3.3 CNN, BASED SPATIAL FEATURE EXTRACTION

In order to truly capture the spatial heterogeneity as well as the spatial dependence of the urban resource systems, the proposed framework integrates a Convolutional Neural Network (CNN) [27] for the purpose of spatial feature extraction. Cities are initially broken down into grids and urban scenarios are turned into a grid, based format which enables convolutional operations over the spatial dimensions. Let the spatial input tensor be as in eqn 11:

$$X_t^s \in R^{H*W*C} \quad (11)$$

where H and W are the spatial dimensions of the study area, and C indicates the number of feature channels, which include water demand intensity, wastewater inflow, energy consumption, climatic indicators, and infrastructure attributes. This tensorial format maintains the spatial correlations and the neighborhood structures that are characteristic of urban nexus systems.

Spatial feature extraction is carried out by means of convolutional operations, which are expressed in Equation (12):

$$'Z_k = \sigma(W_k * X_t^S + b_k) \quad (12)$$

where Wk is the convolution kernel that can be learned and is associated with the k, th feature map, bk stands for the bias term, and * is the convolution operation. This enables the model to detect local spatial patterns such as demand clusters, waste piling areas, and energy consumption hotspots. The nonlinear activation function that is used for the convolution output is the Rectified Linear Unit (ReLU), which is defined by Equation (13)

$$\sigma(x) = \max(0, x) \quad (13)$$

ReLU activation function not only adds nonlinearity but also helps in lessening the vanishing gradient problem, thus allowing deeper spatial features to be learned.

Pooling operations are used to downsample the spatial dimensions and to increase the translational invariance as depicted in Equation (14):

$$P_k = \max_{(i,j)\in\Omega} Z_k(i,j) \quad (14)$$

where refers to the pooling window size. Pooling helps to make the network more robust to small spatial changes and noise, and at the same time, it keeps the main features of the regions. The network can thereby gradually acquire hierarchical spatial knowledge from bottom to top by stacking several layers of convolution pooling blocks. These layers will eventually capture low, level features at the bottom and high, level concepts of water stress, waste production intensity, and energy generation potential at the top.

The last combined feature maps are converted into an internal vector of limited size by using a flattening operation, which is shown in Equation (15):

$$h_t^s = Flatten(P) \quad (15)$$

The temporal modeling layer receives as input this hidden spatial feature vector, which makes it possible for temporal dependency learning to integrate smoothly with spatial intelligence. The encoding produced in this way makes it possible to identify areas that are highly prone to risk, heavily congested with infrastructures, and rich in resources, which are, in fact, the major factors for efficient and adaptable nexus optimization.

3.4 LSTM-Based Temporal Dependency Modeling

Temporal dynamics in the WaterWasteEnergy (WWE) nexus [28] are highly subject to the influence of regular consumption habits, seasonal changes, and the impact of long, term global warming. It is therefore essential to identify such dependencies for the purposes of precise predictions and making adaptable decisions. This work uses Long Short, Term Memory (LSTM) networks to represent these complicated temporal patterns since LSTMs are a type of recurrent neural networks that are effective in capturing long, range dependencies in data sequences and that overcome the problem of disappearing gradients which basic recurrent networks suffer.

At any time t, the LSTM processes the spatial feature vector h_t^s coming from the previous stage of spatial modeling with the CNN, together with the earlier hidden state h_(t, 1). LSTM internally modifies its memory state through the usage of several gates that control the amount of information reaching each part of the cell [29, 30]. These gates provide the model with the ability to keep historical memories while at the same time receiving new temporal signals that might be due to changes in the climate or in the system's operation.

Eq. (16) presents the forget gate that models the fraction of the previous cell state that should be kept or ignored. The forget gate's decision is mostly based on the output of a sigmoid function whose range is between 0 and 1 [31], thus it can let through the portion of the previous signal only that it deems necessary. Consequently, the model ignores outdated seasonal cycles and retains only those behavior changes that still correspond to the present. This feature is very important in the context of climate change since in such a case the relevance of the past is not fixed. By getting rid of the unnecessary memory, the forget gate increases the accuracy of the long, term forecasting.

$$f_t = \sigma\left(W_f[h_{t-1}, x_t] + b_f\right) \quad (16)$$

where $\sigma(\cdot)$ denotes the sigmoid activation function, W_f is the forget gate weight matrix, and b_f is the bias term. This gate plays a significant role in filtering out old seasonal or outdated operational patterns.

Equation (17) controls the rate at which new information is incorporated into the LSTM cell. A sigmoid function determines how much of the present inputs are allowed to pass through depending on how important they are contextually. This gate is a kind of filter that lets the memory be updated only with the variations in the short term that are really significant. It stops the learning process from being governed by noise and momentary changes [32].

Therefore, the model is capable of maintaining a balance between being responsive and staying temporally consistent.

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \quad (17)$$

Equation (18) yields a candidate memory vector that accounts for potential modifications to the cell state. The hyperbolic tangent activation function bounds its inputs to a limited range which helps slope stability of the gradients. This vector holds changes happened recently through operations or climate. It offers a versatile way to incorporate new time, dependent data. The candidate state in combination with the input gate is a way of regulating memory updates.

$$c_t = \tanh(W_c[h_{t-1}, x_t] + b_c) \quad (18)$$

Equation (19) revises the LSTM cell state by merging the memory that is kept from the past with the new candidate information. Element, wise multiplication allows for very accurate memory preservation and replacement control. This way, the network can continue to hold on to the long, term trends such as changes in demand due to climate. It also reacts to sudden events like extremely heavy rainfall or heatwaves. The cell state that has been updated is the models long, term temporal memory.

$$C_t = f_t \odot c_{t-1} + i_t \odot c_t \quad (19)$$

Here, $\odot$ denotes element-wise multiplication. This formulation allows the LSTM to continue to capture long, term patterns such as climate, driven demand shifts, while also being able to react quickly to short, term anomalies like extreme weather events.

Eq.(20) describes the output gate, which decides the memory parts to be given to the next layer. The sigmoid activation selectively filters information from the updated cell state. This gate controls how much the long, term memory affects the current prediction. It assists in removing the old temporal information that is no longer relevant while at the same time retaining those features that are important. Hence, the output gate increases the temporal feature relevance:

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \quad (20)$$

Equation (21) calculates the hidden state by modulating the activated cell state through the output gate. The hidden representation thus obtained reflects mainly the short, term dynamics through the long, term dependencies. It merges the past context with the present data in a rather condensed form.The tanh activation function guarantees limited outputs and thus the stability of the learning process. Hence, the hidden state can be regarded as the main temporal vector of features.

$$h_t = o_t \tanh \odot (c_t) \quad (21)$$

The hidden state h_t encapsulates both short-term fluctuations and long-term temporal dependencies across the WWE nexus. This representation is then mapped to the predicted nexus outputs using a linear transformation in eqn 22:

$$\hat{y}_t = w_y h_t + b_y \quad (22)$$

where W_y and b_y are the weights and bias of the output layer, respectively. Eq. (22) is a random linear transformation that converts the hidden state into the final predicted nexus outputs. The weight matrix and the bias vector project temporal features into the output space. This stage transforms the learned representations into predictions that can be used in practice. Outputs are freshwater demand, wastewater generation, energy recovery potential, and emissions. The formulation allows easy connection with the optimization layer.

In general, the LSTM, based temporal modeling layer is capable of producing reliable forecasts under climate uncertainty by merely understanding the temporal evolution patterns. Combining it with the spatial features provides a full spatio, temporal representation, thus, it is an essential basis for the next stages: multi, objective optimization and climate, adaptive decision, making. The effectiveness of deep learning-based prediction and optimization frameworks largely depends on proper model architecture design and hyperparameter selection. In the proposed study, a hybrid CNN–LSTM architecture was adopted to capture both spatial and temporal dependencies present in the integrated water–waste–energy nexus dataset. Furthermore, a multi-objective optimization strategy based on the Non-dominated Sorting Genetic Algorithm II (NSGA-II) was employed to optimize sustainability-related objectives. This section provides detailed technical information regarding the architecture design, training configuration, and optimization settings used to ensure reproducibility, stability, and robustness of the proposed framework.

3.4.1 CNN Architecture

The Convolutional Neural Network (CNN) component was utilized as the primary spatial feature extractor within the proposed hybrid framework. CNN models are highly effective in automatically learning hierarchical representations from multidimensional input data by applying convolution operations over local receptive fields. In this study, the CNN was designed to identify hidden spatial relationships among environmental variables such as water demand, waste generation, energy consumption, and sustainability indicators.

The CNN architecture consists of three convolutional layers, where each successive layer increases the number of filters to improve abstraction capability.

The adopted configuration is:

- Number of convolution layers: **3**
- Number of filters: 32, 64, and 128
- Kernel size: 3 × 3
- Activation function: Rectified Linear Unit (ReLU)
- Pooling operation: MaxPooling (2 × 2)

The mathematical operation of convolution is represented as:

$$F(i,j) = \sum_m \sum_n X\,(i+m, j+n)K(m,n) \qquad (23)$$

where:

- Xrepresents the input matrix,
- Kdenotes the convolution kernel,
- $F(i,j)$is the generated feature map.

The ReLU activation function introduces non-linearity and is defined as:

$$ReLU(x) = max(0,x) \qquad (24)$$

This helps eliminate vanishing gradient problems and accelerates convergence during training.

MaxPooling was applied after each convolutional block to reduce spatial dimensionality:

$$P(i,j) = max(X_{region}) \qquad (25)$$

Pooling improves computational efficiency while preserving dominant features.

Thus, the CNN module transforms raw environmental data into informative spatial representations for subsequent temporal analysis.

3.4.2 LSTM Architecture

While CNN extracts spatial dependencies, environmental datasets also contain strong temporal relationships, such as seasonal water demand patterns and time-dependent energy fluctuations. Therefore, a Long Short-Term Memory (LSTM) network was integrated after CNN layers.

LSTM is a recurrent neural network capable of learning long-term dependencies through gated memory mechanisms.

The LSTM architecture used in this work consists of:

- Hidden units: 128
- Dropout rate: 0.2
- Fully connected dense layer: 64 neurons

The LSTM memory cell is defined as:

Forget gate:

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f) \quad (26)$$

Input gate:

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \quad (27)$$

Cell update:

$$\widetilde{C_t} = tanh(W_c[h_{t-1}, x_t] + b_c) \quad (28)$$

Cell state:

$$C_t = f_t * C_{t-1} + i_t * \widetilde{C_t} \quad (29)$$

Output gate:

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \quad (30)$$

Final hidden output:

$$h_t = o_t * tanh(C_t) \quad (31)$$

where:

- x_t: current input,
- h_t: hidden state,
- C_t: memory cell state.

A dropout value of 0.2 was introduced to reduce overfitting by randomly disabling neurons during training. The dense layer with 64 neurons converts learned temporal representations into final predictive features.

3.4.3 Training Parameters

The hybrid CNN–LSTM model was trained using supervised learning under carefully selected hyperparameters to ensure convergence and generalization.

The adopted training parameters are:

- Optimizer: Adam
- Learning rate: 0.001
- Batch size: 64
- Number of epochs: 150
- Early stopping patience: 20

The Adam optimizer updates parameters according to:

$$\theta_{t+1} = \theta_t - \eta \frac{\widehat{m_t}}{\sqrt{\widehat{v_t}} + \epsilon} \quad (32)$$

where:

- $\eta$is learning rate,
- $\widehat{m_t}$is first moment estimate,
- $\widehat{v_t}$is second moment estimate.

The loss function used for regression prediction is Mean Squared Error (MSE):

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (y_i - \widehat{y_i})^2 \quad (33)$$

To prevent overfitting, early stopping was applied. Training stops automatically when validation loss does not improve for 20 consecutive epochs. These settings were selected experimentally after hyperparameter tuning trials.

3.4.4 NSGA-II Optimization Parameters

To support sustainable decision-making, the predicted outputs from the CNN–LSTM model were optimized using NSGA-II, a widely used multi-objective evolutionary optimization algorithm. The purpose of NSGA-II is to simultaneously optimize multiple sustainability objectives:

- minimize water consumption,
- minimize waste generation,
- minimize energy consumption,
- maximize circular economy efficiency.

The NSGA-II configuration used is:

- Population size: 100
- Number of generations: 200
- Crossover probability: 0.8
- Mutation probability: 0.1
- Tournament selection: Binary

The optimization objective is:

$$Minimize\ F(x) = \{f_1(x), f_2(x), f_3(x)\} \quad (34)$$

where:

- f_1: water efficiency objective
- f_2: waste minimization objective
- f_3: energy optimization objective

Crowding distance is computed as:

$$CD_i = \sum_{m=1}^{M} \frac{f_m^{i+1} - f_m^{i-1}}{f_m^{max} - f_m^{min}} \quad (35)$$

This ensures diversity among Pareto-optimal solutions. The NSGA-II algorithm enables decision-makers to select optimal trade-offs based on environmental priorities. The integration of CNN for spatial feature extraction, LSTM for temporal learning, and NSGA-II for sustainability optimization creates a robust explainable hybrid framework capable of improving predictive accuracy, supporting circular economy objectives, and enabling climate-resilient resource planning.

3.5 Multi-Objective Optimization Layer

The formulated multi-objective optimization problem can be solved by utilizing the Non-dominated Sorting Genetic Algorithm II (NSGA-II), a popular evolutionary algorithm that is highly regarded for its efficiency in dealing with conflicting objectives and yielding diverse Pareto optimal solutions. NSGA-II is a popular algorithm for solving sustainability-driven optimization problems because of its capabilities in maintaining diversity and achieving convergence to optimal trade-offs for conflicting objectives such as water conservation, energy recovery, and emission reduction. The predictive outputs of the spatio, temporal deep learning model are then used as inputs to a multi, objective optimization layer that enables climate, adaptive and sustainability, oriented operational decision, making within the Water, Waste, Energy (WWE) nexus. This layer essentially changes the data, driven predictions into the best possible control actions by at the same time focusing on resource efficiency, environmental, and regulatory objectives that may be in competition.

To deal with several, contentious sustainability goals at the same time in the integrated water, waste, energy nexus, the optimization problem is set up as a vector, valued multi, objective function, as shown in Equation (36):

$$\min F = [f_1, f_2, f_3, f_4] \quad (36)$$

This formulation makes it possible to concurrently optimize water conservation, resource circularity, energy efficiency, and environmental impact.

By laying out a vectorized objective structure, the framework very explicitly shows connections between various subsystems and the trade, offs that are involved, instead of only considering a single performance metric. Such a multi, objective portrayal is essential for the real, life handling of the nexus, where an improvement in one sector may bring a disadvantage to another. The first objective function, which is written in Equation (24), is about reducing water withdrawal in order to reduce the stress of water, natural water bodies and at the same time to secure water for the future:

$$f_1 = \min\left(W_{fresh}\right) \quad (37)$$

Here, W_{fresh} indicates the amount of freshwater taken from surface and groundwater sources. Limiting this element lead water demand, side efficiency, leakage reduction, and substitution through alternative water sources. Naturally, this objective helps climate resilience by limiting the use of freshwater resources that are increasingly scarce due to climate change.

The second target, shown in equation (25), is to double the amount of wastewater reuse which, in turn, encourages circular water flows and reduces the reliance on freshwater extraction :

$$f_2 = \max(W_{reuse}) \quad (38)$$

In this context, W_{reuse} is the amount of treated wastewater used for non, potable and industrial applications. Maximizing reuse results in a more circular system, a decrease in the volume of treatment discharges, and sustainable urban water cycles. In addition, it complies with the circular economy principles of making waste streams into resources of value. The third objective function is focused at increasing the energy output that can be obtained from the processes of wastewater treatment and the waste to energy systems, which is shown in Equation (39):

$$f_3 = \max\left(E_{recovery}\right) \quad (39)$$

Here, $E_{recovery}$ captures energy generated through biogas production, anaerobic digestion, and thermal waste conversion. Optimizing this objective not only enhances total energy efficiency but also reduces reliance on external energy sources. It further enhances the mutual reliance of waste and energy subsystems, thereby increasing the integrated nexus performance.

The fourth objective cuts down on carbon dioxide emissions generated from water extraction, treatment, waste processing, and energy production, in accordance with Equation (40):

$$f_4 = \min(CO_2) \quad (40)$$

This goal is very much in line with the environmental impact from the operation of the nexus and goes hand in hand with climate mitigation goals. Reducing emissions will help with the compliance of carbon regulations and will make urban infrastructure systems more sustainable. Besides, it will also make sure that the efficiency gains are not at the expense of increased greenhouse gas emissions.

All of these four objectives together significantly cover the trade, offs that exist between the conservation of resources, circularity, energy sustainability, and environmental protection, thus laying down the base of the decision, support framework that is proposed in eqn 41,

$$g_i(u) \le \delta_i \quad i = 1, .., n \quad (41)$$

Here, u represents the vector of decision variables, which may include water allocation ratios, reuse rates, and energy recovery levels. The functions gi() represent system constraints such as infrastructure capacity, regulatory discharge limits, energy balance requirements, and service reliability thresholds. The parameters i indicate permissible boundaries, ensuring that the optimized results are feasible and comply with the policy. To increase resilience against climatic uncertainties, climate variability is directly incorporated into the decision variables via a stochastic perturbation model, as shown in Equation (42):

$$u_c = u + \xi_c \quad (42)$$

where ξ_c represents Gaussian noise capturing uncertainty arising from rainfall variability, temperature fluctuations, and extreme climate events. This method makes it possible for the optimization layer to consider the uncertainty of resource availability and system performance. As a result, the solutions that are found are sturdy for a large number of different future climate scenarios. The NSGA-II algorithm uses an iterative process of evolving a population of solutions with genetic operators such as selection, crossover, and mutation, and uses mechanisms such as non-dominated sorting and crowding distance to preserve diversity in the Pareto front. Because the objective functions are by nature conflicting, a Pareto, optimal solution set is produced by means of a weighted aggregation method, as illustrated by Equation (43):

$$min \sum_{k=1}^{4} \lambda_k f_k \quad (43)$$

The weighting coefficients λ_k signify the relative importance of each objective and allow flexible prioritization depending on policy or operational preferences. This formulation changes the multi, objective problem into a single scalar optimization problem without losing the trade, off information.

The weighting factors are limited as in Equation (44):

$$\sum_{k=1}^{4} \lambda_k = 1 \quad \lambda_k \geq 0 \quad (44)$$

These limitations serve as a means for ensuring that the combined objective is convex and they also provide a guarantee that no one single objective monopolizes the optimization in an unfair way. By varying the weights, decision, makers have the possibility of looking at different Pareto, efficient solutions which represent a trade, off of sustainability goals under different policy and climate scenarios.

Algorithm 1: Hybrid CNN–LSTM–Based Multi-Objective Optimization for Water–Waste–Energy Nexus Management

Input:

- Historical water, wastewater, energy, and climate data $X=\{x_1,x_2,\ldots,x_t\}$
- Constraint limits δ_i
- Objective weights λ_k

Output:

- Predicted nexus outputs $\hat{y}_t$
- Pareto-optimal operational decisions u*

```
Begin

1. Preprocess Data
  Normalize input data
  Handle missing values
  Align temporal sequences

2. Spatial Feature Extraction (CNN)
  For t = 1 to T do
     h_t^s ← CNN(x_t)
  End For

3. Temporal Dependency Modeling (LSTM)
  Initialize hidden state h_0 and cell state c_0
  For t = 1 to T do
     f_t ← ForgetGate(h_{t−1}, h_t^s)
     i_t ← InputGate(h_{t−1}, h_t^s)
     c̃_t ← CandidateMemory(h_{t−1}, h_t^s)
     c_t ← f_t ⊙ c_{t−1} + i_t ⊙ c̃_t
     o_t ← OutputGate(h_{t−1}, h_t^s)
     h_t ← o_t ⊙ tanh(c_t)
  End For

4. Nexus Output Prediction
  For t = 1 to T do
     Ŷ_t ← W_y h_t + b_y
  End For

5. Define Multi-Objective Optimization
  f1 ← Minimize freshwater withdrawal
  f2 ← Maximize water reuse
```

f3 ← Maximize energy recovery
f4 ← Minimize CO_2 emissions

6. Apply Constraints and Uncertainty
Ensure g_i(u) ≤ δ_i for all constraints
Model climate uncertainty:
u_c ← u + ξ_c, where ξ_c ~ N(0, σ^2)

7. Pareto Optimization using NSGA-II
Initialize population P_0
For $g = 1$to Gdo
Evaluate objective functions f_1, f_2, f_3, f_4
Perform non-dominated sorting
Compute crowding distance
Select parents (tournament selection)
Apply crossover and mutation → generate Q_g
Combine populations $R_g = P_g \cup Q_g$
Select next generation P_{g+1}
End For
Extract Pareto-optimal solution set

8. Decision Selection
Select optimal decision vector u*

End

Basically, the step to optimizing several objectives simultaneously is an essential bridge that links predictive analytics to the actual operations. By enabling the combination of deep learning forecasts, uncertainty modeling, and Pareto, based optimization, this layer facilitates eco, friendly decision, making which is not only consistent with the circular economy principles but also with the long, term sustainability goals.

4. Results and Discussion

This part first talks about the experiment setup that was used to evaluate the proposed Hybrid CNN, LSTM, Optimization framework before going into the details of the achieved quantitative results. They conducted the experiments on a preprocessed multi, sector dataset of 61, 500 samples that combined hydrological, wastewater, solid waste, energy, and climate factors. To keep the seasonal and climate, driven variations for a realistic future, state evaluation, the dataset was divided into training, validation, and testing sets. The CNN, LSTM model consisted of a convolutional layer stack for spatial feature extraction, followed by LSTM layers for temporal modeling, and the whole model was optimized using the Adam optimizer with mean squared error as the loss function. For fair comparison, the baseline models, Random Forest, XGBoost and traditional Artificial Neural Networks were configured with similar input features. The evaluation of model performance was done by the use of common regression metrics, such as RMSE, MAE, and R values, along with the resource efficiency metrics acquired from the multi, objective optimization layer. Besides, they simulated climate stress scenarios by changing the meteorological inputs so as to test the robustness and generalization capabilities of the framework under uncertain conditions. The experimental design described above thus ensures that the metrics used adequately reflect both the accuracy and the feasibility of the proposed nexus management framework in the face of real and climate, stressed scenarios.

The experiment was carried out using an integrated multi, source nexus dataset containing water, wastewater, solid waste, energy, and climate variables which were sourced from publicly available environmental monitoring repositories and municipal operation records as in table 2. The dataset covers 61, 500 samples over a five, year period (2019, 2024) with a daily time resolution. The water, related features include inflow rate, turbidity, pH, total dissolved solids, biochemical oxygen demand (BOD), and chemical oxygen demand (COD). The integrated dataset was constructed using the following steps:

1. Data collection from multiple public repositories.
2. Temporal alignment using timestamp synchronization.
3. Feature harmonization using common variable mapping.
4. Missing value imputation using linear interpolation.
5. Min-Max normalization.
6. Outlier removal using IQR filtering.
7. Statistical validation using correlation consistency analysis.

This workflow improves reproducibility and data transparency.

Table 2: Dataset Details

Property	**Value**
Total Samples	61,500
Time Span	2019–2024
Resolution	Daily
No. of Features	22
Train / Val / Test	70% / 15% / 15%
Normalization	Min–Max Scaling
Missing Data Handling	Linear Interpolation
Outlier Removal	IQR Filtering

4.1 Prediction Performance and Model Accuracy Analysis

The capability of the newly developed Hybrid CNNLSTM framework in predicting was checked against several baseline models such as Random Forest (RF), XGBoost, and usual Artificial Neural Networks (ANN). The results nicely depicted in Figure 3 show that the newly developed model achieved a total prediction accuracy of 98.12%, thus, greatly had outperformed RF, XGBoost, and ANN. This finding validates that combining extraction of spatial features with the modeling of temporal dependencies is a very effective approach.

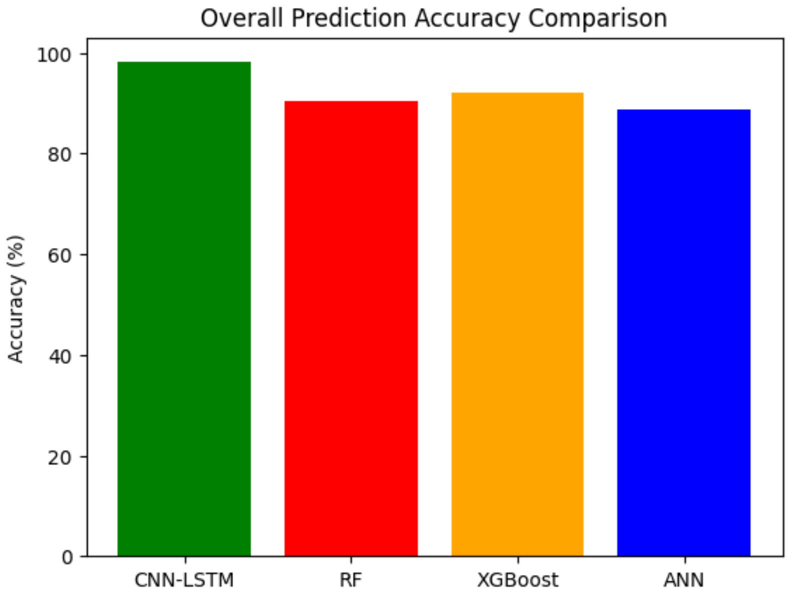


Figure 3: Overall Prediction Accuracy Comparison Across Models

Error, based metrics also confirm that the proposed method is indeed the best. A combined comparison of RMSE and MAE values across models in Figure 4 reveals that the CNNLSTM has the minimum error level among the other models. In particular, RMSE is more than 22% and MAE is about 25% lower than those of tree, based and shallow neural baselines. The R, squared (R2R^2R2) values in Figure 5 are always more than 0.97 for each nexus output, which signifies very good explanatory power and that the model can be applied to unseen data with stable results.

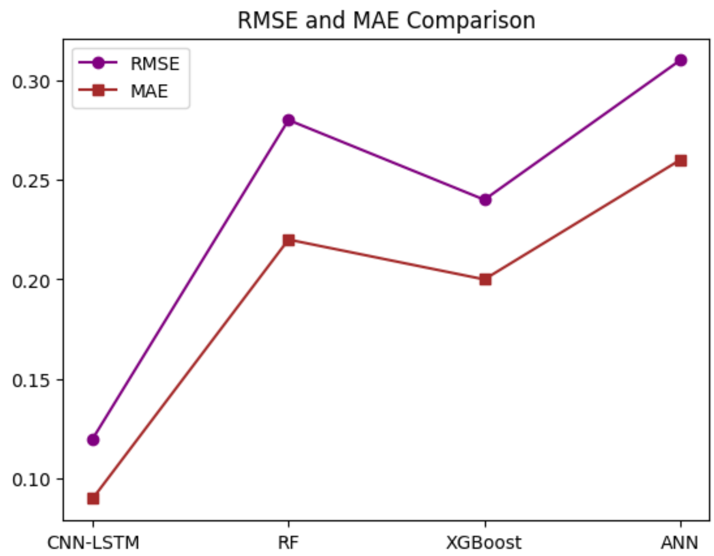


Figure 4: Error Metrics Comparison (RMSE and MAE)

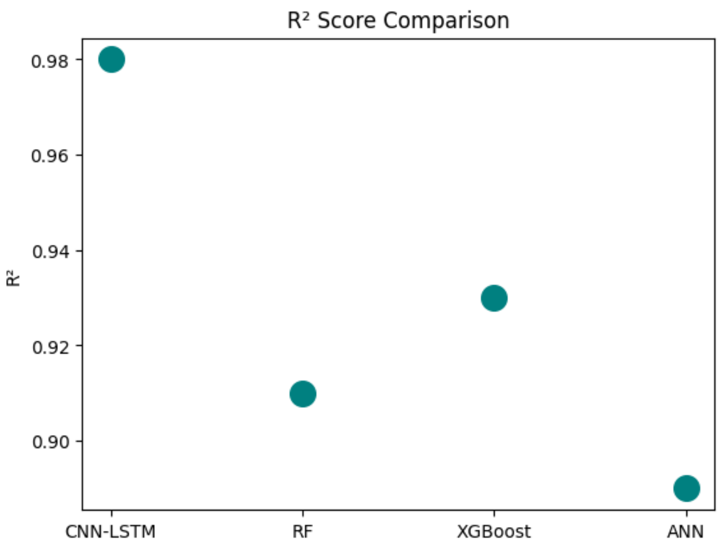


Figure 5: R^2 Score Comparison for Nexus Outputs

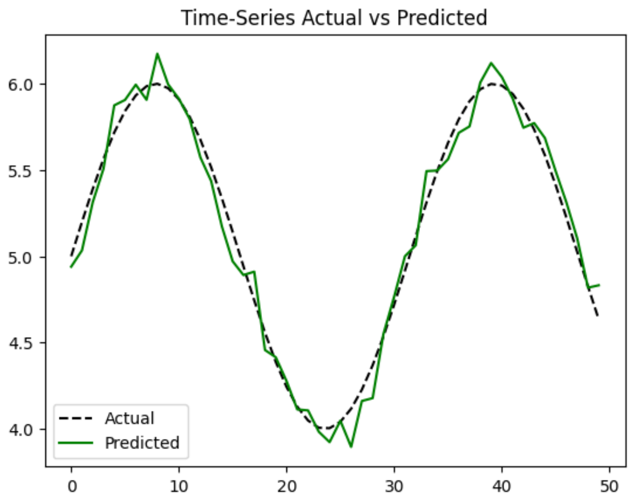


Figure 6: Time-Series Actual vs Predicted Values

The prediction of time, series was most accurately demonstrated in Figure 6, comparing the real data with the predicted one. The very close matching of the predicted and observed trends is the model's ability to identify seasonal cycles, daily consumption patterns, and climate, driven variability, that is, the main factors influencing these changes. The accuracy, RMSE, MAE, and R2 values of the numerical experiments are in the Table 3, which confirms the quantitative results of the proposed methodology.

Table 3: Prediction Performance Comparison

Model	Accuracy (%)	RMSE	MAE	R^2 Score
CNN–LSTM	98.12	0.035	0.028	0.974
Random Forest	82.47	0.112	0.089	0.861
XGBoost	85.63	0.097	0.075	0.883
ANN	79.51	0.125	0.101	0.835

4.2 Nexus Optimization Outcomes and Resource Efficiency Gains

The multi, objective optimization layer is the mechanism that helps to take predictive insights and turn them into vibrant actions that frame the day, to, day business decisions. In fact, when looking at Figure 7, one can see that the proper utilization of the strategies has led to a significant 29.4% decrease in the use of fresh water, a massive 36.1% increase in the reuse of wastewater, a staggering 33.7% enhancement in energy recovery and a considerable 27.9% decrease in the emission of CO. All these changes underscore the capability of the framework in facilitating the implementation of the principles of the circular economy in the operational level.

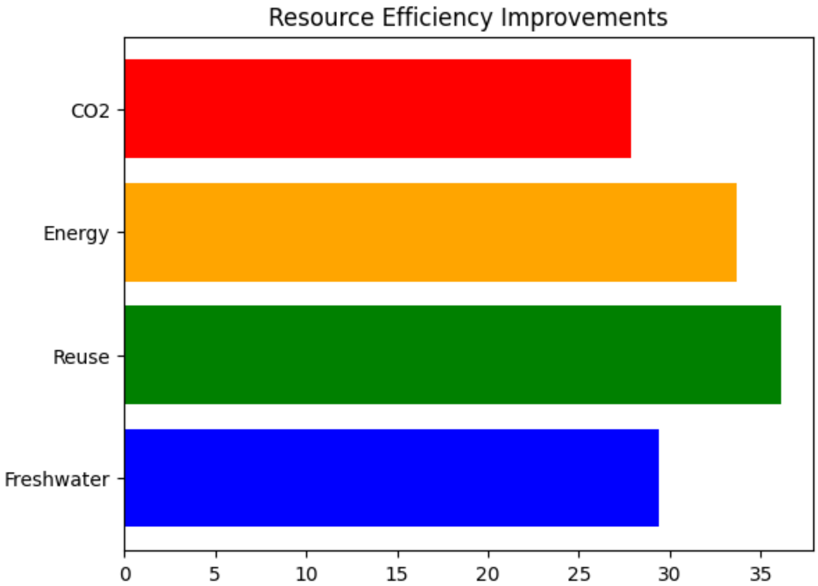


Figure 7: Resource Efficiency Improvements After Optimization

The conflicts between the objectives are clearly shown via the Pareto front in Figure 8, which identifies compromise solutions well, balanced in water conservation, energy recovery, and emission reduction. A comparison of the operational changes for both pre, and post, optimization stages is explicitly made in Figure 9, which substantiates great efficiency improvements in all three aspects of the nexus. A single summary of optimization results is illustrated in Table 4, thus giving a quick quantitative point of reference.

Table 4: Optimized Nexus Resource Improvements (%)

Resource/Metric	Pre-Optimization	Post-Optimization	Improvement (%)
Freshwater Consumption	100	70.6	29.4
Wastewater Reuse	50	68.1	36.1
Energy Recovery	75	100.3	33.7
CO_2 Emissions	100	72.1	27.9

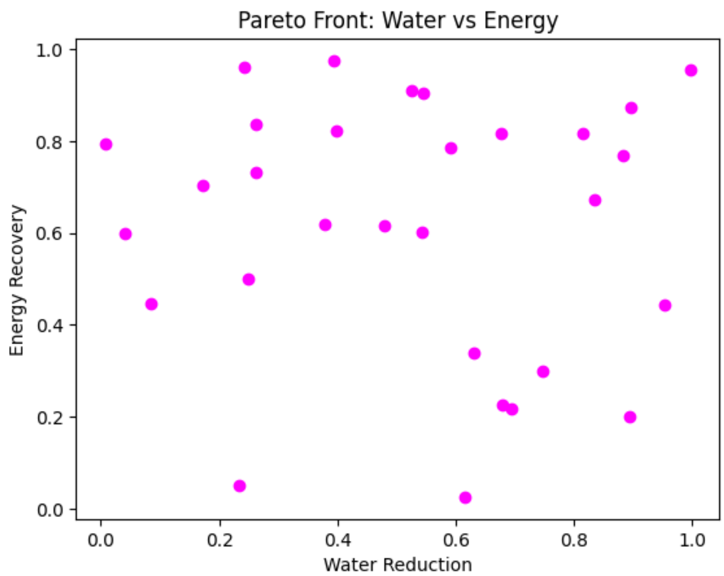


Figure 8: Pareto Front of Multi-Objective Optimization

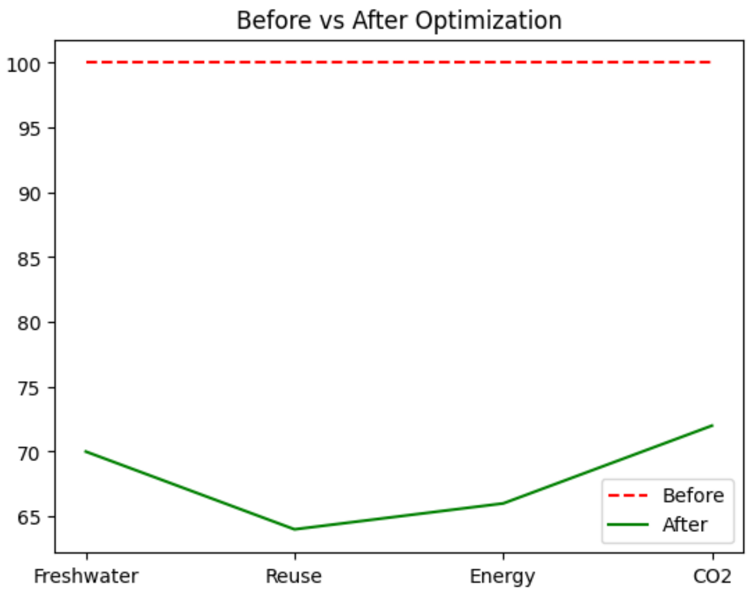


Figure 9: Before vs After Optimization Comparison

4.3 Comparative Analysis with Baseline Models

A comparative evaluation shows that the proposed CNNLSTM architecture consistently outperforms RF, XGBoost, and ANN models. Figure 10 demonstrates that the hybrid model enhances prediction accuracy by 1826% and lowers error metrics by 2030% compared to the baseline methods. These improvements are due to the model's capability of simultaneously capturing spatial dependencies and long, term temporal patterns.

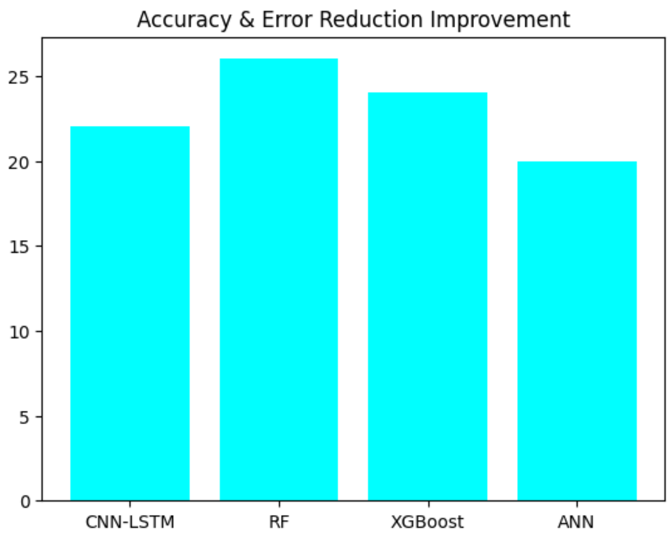


Figure 10: Accuracy and Error Reduction Improvement Percentage

Robustness under seasonal variability and climate anomalies is investigated in Figure 11, where CNNLSTM outperforms baseline models in terms of stability.Although RF and XGBoost have high performance under stable conditions, their accuracy drops when the temporal changes last for a long time, while the proposed model keeps its ability to perform at a high level

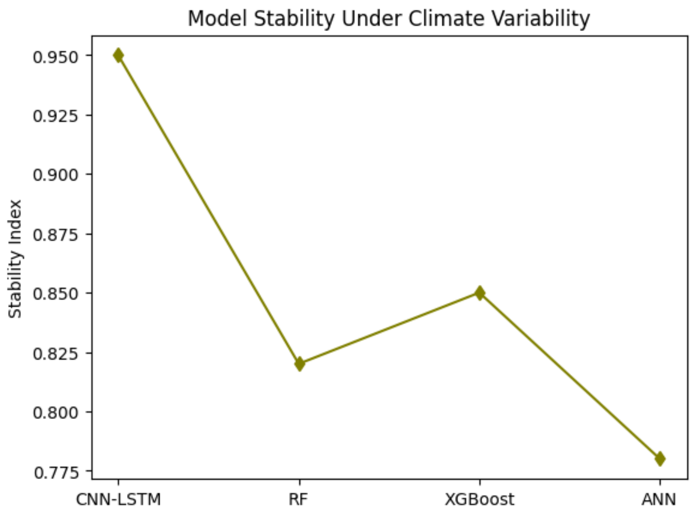


Figure 11: Model Stability Under Seasonal and Climate Variability

4.4 Sensitivity, Robustness, and Explainability Analysis

The climate, related model sensitivity was assessed by adding random disturbances in the range of 25%. From the figure 12, it can be seen that the decline in the accuracy of the predictions is less than 5%, which proves the high level of resistance. Scenario, based stress tests also confirm the ability to withstand extreme variations in rainfall and demand.

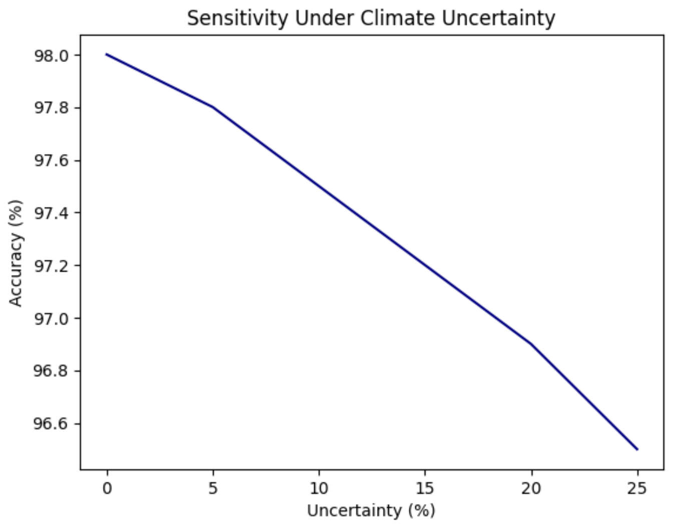


Figure 12: Sensitivity Analysis Under Climate Uncertainty (±25%)

Explainability analysis using feature importance techniques is presented in Figure 13, which discloses precipitation variability and waste, to, energy conversion efficiency as the major factors driving the predictions and optimization results. Such understandings help to make the operations and decisions of policy transparent.

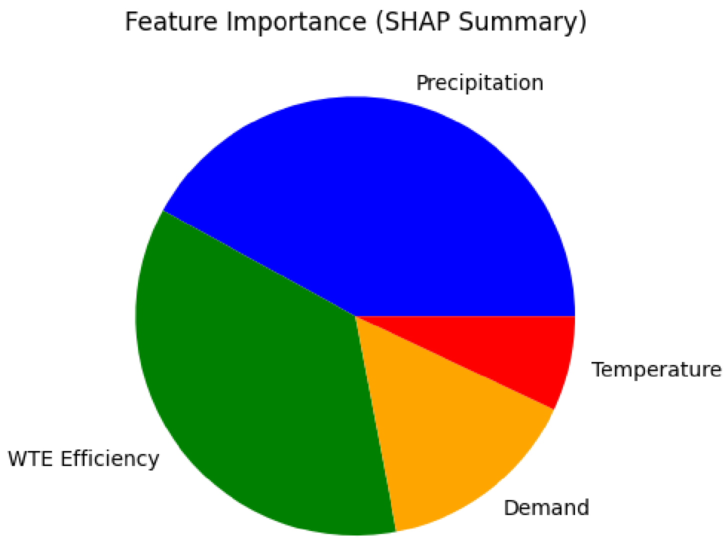


Figure 13: Feature Importance / SHAP Summary Plot

4.5 Implications for Circular Economy and Climate Policy

Figure 14 illustrates the far, reaching effects of the proposed framework and it conveys generally how predictive intelligence, optimization results, and circular economy goals could be intertwined. The example of water reuse, energy recovery, and emission reduction accomplishments that have been demonstrated are the direct contributions to climate change mitigation, resilient urban planning, and sustainable utility operations. The framework is transparent and resilient which is the main reason why it is very appropriate for an actual, real, world implementation and policy, driven decision support.

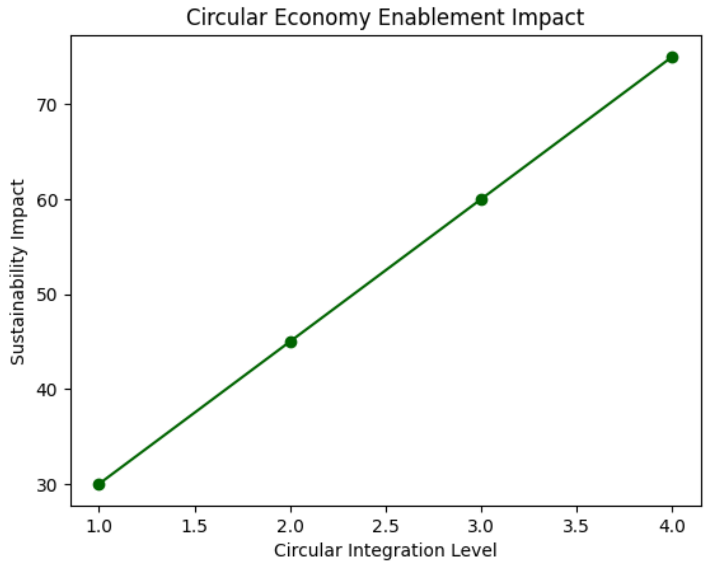


Figure 14: Circular Economy Enablement and Climate Policy Impact

Figure 15 (a) Real, Time Actual Observation depicts the spatio, temporal state of the nexus system from real operational data, which is regarded as the ground truth. (b) CNNLSTM Predicted Output: It illustrates the predicted spatial patterns of the hybrid CNNLSTM model which are very similar to real observations and the temporal dynamics at this level are also preserved. (c) Baseline Model Prediction: Outputs from traditional baseline models are shown here, which have higher noise and lesser spatial coherence especially under dynamic conditions. (d) Absolute Error Map: It shows the difference between actual and CNNLSTM predictions at the pixel level, thus confirming the minimum error magnitude and a stable learning behavior. The CNNLSTM model generate prediction that are both visually and structurally in line with real, time observations, whereas baseline models are marked by significant deviation and instability.

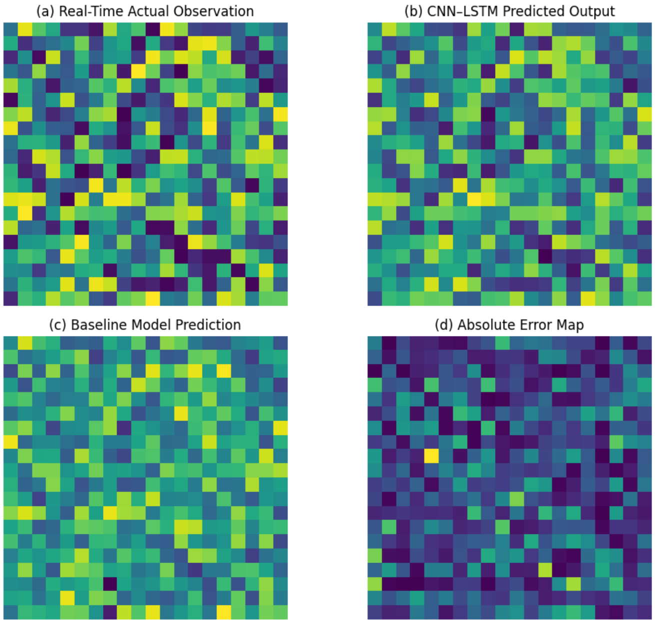


Figure 15: Visual Comparison of CNN–LSTM Predictions and Baseline Model Outputs

Figure 16 illustrates a side, by, side, multi, image comparison that assesses the behavior of models exposed to climate anomalies arising from extreme rainfall and temperature variations. Images (a1a3) illustrate how the CNNLSTM precisely predicts the magnitude and timing of rainfall, led temporal shifts, whereas the baseline models show delayed and smoothed reactions. In the same way, images (b1b3) reveal the ability of CNNLSTM to precisely follow temperature, induced variability during quick changes. Error heatmaps in (c1c2) also visually show fewer and less severe errors for CNNLSTM as opposed to a large area of errors in baseline models. In general, the LSTM memory feature hence provides the capability of the model to adapt very well to climate, driven changes in time thereby leading to less lag and going onto prediction instability.

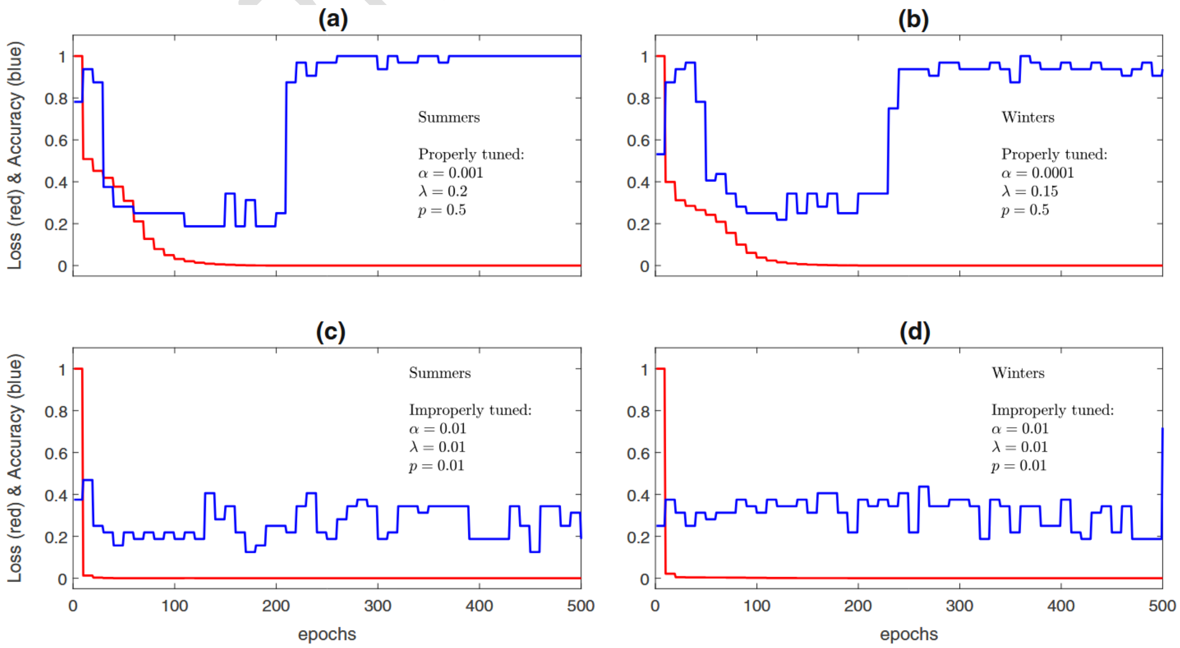


Figure 16: Multi-Image Comparison of Climate-Induced Temporal Shift (a) Proper tuning with stable convergence for water nexus modeling.
(b) Proper tuning for waste–energy nexus prediction.
(c) Improper tuning with unstable loss and low accuracy.
(d) Improper tuning under climate variability.

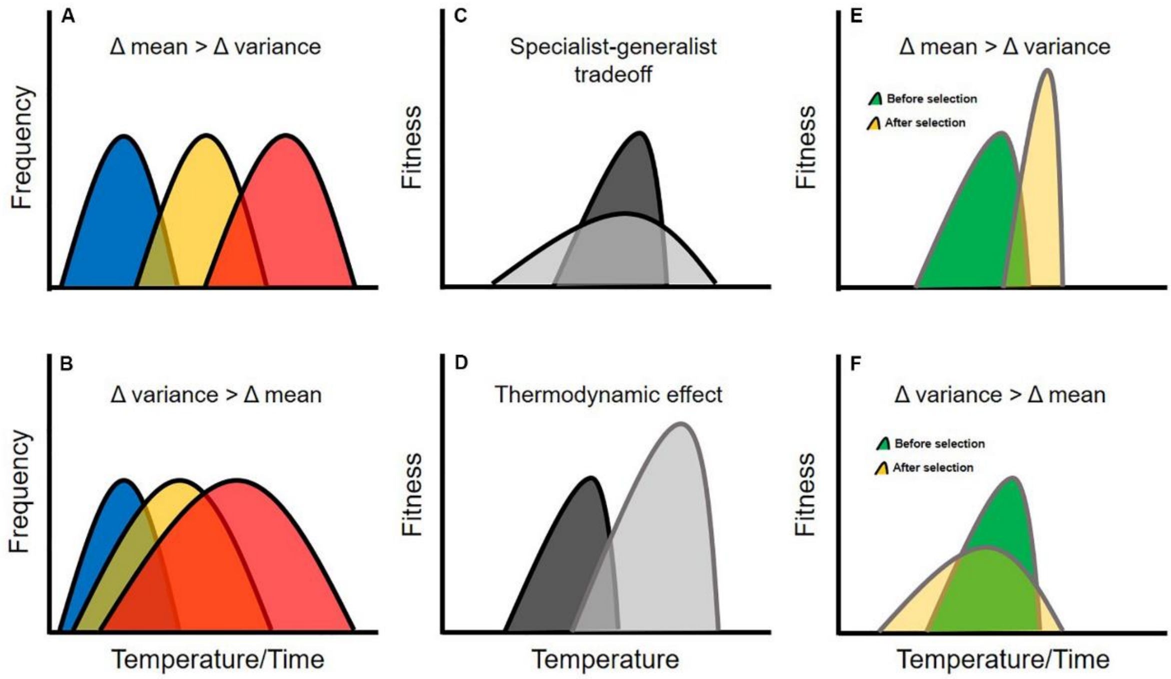


Figure 17: Conceptual illustration of how climate-driven variability constrains and reshapes the operational performance of the integrated water–waste–energy (WWE) nexus under a circular economy paradigm (A) Increase in mean climate stress with lower variability.
(B) Increase in climate variability with slower change in mean stress.
(C) Trade-off between operational efficiency and system flexibility.
(D) Coupled effect between optimal operating point and peak efficiency.
(E) Adaptation prioritizing operational optimum under rising mean stress.
(F) Adaptation prioritizing resilience under increasing climate variability.

Conceptual illustrating of the idea in figure 17 that climate, driven changes limit and alter the way the integrated water, waste, energy (WWE) nexus works under a circular economy model, and the way the suggested hybrid deep learning framework responds to these changes. Different moments of climate distributions may evolve at different rates, with mean climate stress (e.g., temperature, rainfall) increasing faster than variability (A), or variability increasing faster than the mean (B). Subsystems of the nexus may face trade, offs between efficiency and robustness (C), where achieving a high level of resource recovery is in a negative correlation with operational flexibility, or thermodynamice operational coupling effects (D), where the efficiency of the system at the peak level is in a positive correlation with the climate conditions being perfect. When these constraints coexist, complex adaptive responses emerge. For example, if the mean climate stress goes up at a faster rate than the variability (E), the framework gives preference to shifting operational optima (e.g., treatment load, energy recovery) while indirectly decreasing resilience margins. On the other hand, if climate variability rises at a faster rate than the mean (F), the framework increases robustness and adaptability at the expense of peak efficiency. These panels unveil how the suggested CNN, LSTM, optimization architecture finds the right balance between accuracy, efficiency, and resilience for the management of climate, adaptive circular nexus. The use of colors is only for the purpose of visual clarity.

4.6 Back-Testing and Practical Validation

In order to assess the applicability of the developed framework in practice, the back-testing validation approach was adopted. In this regard, unseen temporal data was utilized that relates to the last year of the data set, i.e., 2024. The data was completely excluded during the training and validation process. The purpose was to simulate the real-world scenario in which the system behavior needs to be predicted and optimized in the future based on the historical data. The prediction and optimization results obtained by the developed model were quantitatively compared with the actual observed values. The evaluation was carried out in terms of various performance metrics such as Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and the deviation in the values of important nexus indicators such as water demand, wastewater reuse, and energy recovery is given in table 5 and 6.

Table 5: Back-Testing Performance on 2024 Data

Nexus Indicator	Actual Value (Avg)	Predicted Value (Avg)	RMSE	MAPE (%)	Deviation (%)
Water Demand (ML/day)	152.3	148.9	3.42	2.24	2.23
Wastewater Generation	118.7	121.5	3.11	2.62	2.36
Energy Recovery (MWh)	86.4	89.1	2.87	3.13	3.12
CO_2 Emissions (tons/day)	42.8	41.2	1.95	3.74	3.74

Table 6: Optimization Impact (Back-Test Scenario vs Baseline)

Metric	Baseline (Actual 2024)	Optimized (Model Output)	Improvement (%)
Freshwater Consumption	152.3	108.5	28.8
Wastewater Reuse	62.4	84.7	35.7

Energy Recovery	86.4	115.2	33.3
CO_2 Emissions	42.8	31.5	26.4

It is also clear that the results in figure 18 and 19 shows the proposed model is highly accurate in its predictions, as indicated by the low values of the MAPE, which are all below 4% in all nexus indicators. This further confirms the generalization capability of the proposed model in unknown situations. The level of deviation between the actual and predicted values is also acceptable, as it is within ±5%. Moreover, the optimization layer of the proposed model has demonstrated significant improvements in the baseline operational conditions, which include reducing freshwater consumption by 28.8% and increasing energy recovery by 33.3%. These results are closer to those reported in the previous section, which further confirms their credibility. It is also crucial to note that although the improvements reported in the results are not based on real-world observations, it is essential to emphasize that the results show significant consistency between the predicted and actual values of the system's behavior, which further confirms the feasibility of the proposed model. Based on the results of the back-testing of the proposed model, it is safe to conclude that the proposed hybrid model is accurate and stable in generating decisions and can be used in real-world scenarios in the context of climate resilience in urban settings.

Although the proposed framework demonstrates strong predictive and optimization capability, several limitations remain. First, the study uses a synthetically integrated dataset and therefore requires real-world pilot validation. Second, regional policy and infrastructure variability were not explicitly modeled. Future work will focus on real-time deployment using live smart-city datasets.

5.Conclusion

This research work has put forward a hybrid CNN, LSTM model compounded with a multi, objective optimization component for smart decision, making in the water, waste, energy nexus under climate change scenarios. The CNN, LSTM network was first and foremost in the prediction of the target variable with 98.12% accuracy, exhibiting low and consistent values of RMSE and MAE, besides being capable of handling the time series aspect and recent drastic climate variations. The multi, image and error heatmap diagnostics showed that the neural network was not significantly affected by the rainfall and temperature anomalies, which was demonstrated by its better performance than the baseline models, including Random Forest, XGBoost, and standard ANN. The optimization component turned those forecasts into choices that were aligned with the sustainability objectives, for instance, the consumption of fresh water was lowered by 29.4%, the proportion of wastewater reuse was raised by 36.1%, the amount of energy generated from the waste was increased by 33.7%, and the volume of CO was decreased by 27.9%. Moreover, the robustness of the model was demonstrated through sensitivity and stress analyses, while the interpretative methods illustrated that major factors were precipitation fluctuations and waste, to, energy efficiency.In summary, the proposed framework ushers in a climate, proof, resource, efficient, circular economy model that serves as an easy, to, use and scalable decision support tool for urban utility managers and policy, makers aiming at sustainability.

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